REVISTA FORESTAL MESOAMERICANA KURÚ

Artículo científico

Revista Forestal Mesoamericana Kurú (Costa Rica) Volumen 11, n°27, Julio, 2014 ISSN: 2215-2504

Recibido: 25/02/2014 Aceptado: 03/03/2014

Estimating aboveground biomass for *Eucalyptus saligna Sm.* and *Eucalyptus camaldulensis Dehn* in the center region of Costa Rica

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Abstract

The contribution of forests as climate change mitigation sinks through growth production calls for the accurate determination of their biomass production, therefore it is necessary to to evaluate variables such as weight of dry leaves, diameter at breast height (DBH) , diameter at stump height (DSH) and total height and their effect on individual aboveground biomass. The analysis was conducted at the Technological Institute of Costa Rica (TEC) located in the province of Cartago- Sampling consisted on 31 sampling of *Eucalyptus saligna* and *Eucalyptus camaldulensis* , in order to estimate a linear regression model to predict average tree biomass. The final model obtained for biomass was $\widehat{Biomasa_i} = e^{2,6915+2,1338*\sqrt{DSH_i}}$, with a coefficient of determination of 0,9061. We recommend a study to help determine the biomass and soil organic matter to provide a complete inventory of biomass for a given area.

Resumen

La contribución de los bosques como ecosistemas en la mitigación del cambio climático mediante la producción de biomasa, hace necesario la realización de estudios sobre los factores que puedan ayudar a determinar esta producción. Por ello se desea evaluar si las variables: peso de las hojas secas, diámetro a la altura del pecho (DAP), diámetro a la altura del tocón (DAT) y altura total, tienen efecto sobre la biomasa aérea de un árbol. El análisis se realizó en el sector sur del Instituto Tecnológico de Costa Rica (TEC), ubicado en la provincia de Cartago, se llevó a cabo un muestreo destructivo de 31 árboles de las especies: *Eucalyptus Saligna* y *Eucalyptus Camaldulensis*, con el objeto de estimar un modelo de regresión lineal que sea de utilidad para predecir la biomasa aérea promedio de un determinado árbol. El modelo final obtenido

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Key words: *Eucalyptus saligna*, *Eucalyptus camaldulensis*, biomass, linear regression, model, Costa Rica.

para biomasa fue $\widehat{Biomasa_i} = e^{2{,}6915+2{,}1338*\sqrt{Dat_i}}$, con un coeficiente de determinación de aproximadamente 0.9061. Se recomienda realizar estudios que ayuden a determinar la biomasa del suelo y de la materia orgánica para contar con un inventario más completo de biomasa en una determinada zona.

Palabras clave: *Eucalyptus saligna*, *Eucalyptus camaldulensis*, biomasa, regresión linear, modelo, Costa Rica.

Introduction

In order to mitigate climate change and its impacts, we need to reduce our emissions drastically. This requires strong incentives that take the form of a combination of standards, taxes and carbon markets. In order to meet the envisaged goals, these instruments will have to be put in place at both national and international levels (Delbosc & de Perthuis, 2009). The effects of different forest management regimes on forest, carbon stocks are often studied with simulation models, which are seen especially valuable for the estimation of carbon stock changes (Palosuo, T., Peltoniemi, M., Mikhailov, A., Komarov, A., Fauberta, P., Thüriga E., & Linder, M., 2008). In July 2007, Costa Rica committed itself to achieve carbon neutrality by the year 2021. From that event, the government has worked to establish the foundations to achieve this goal. The main measures taken in this regard has defined its National Climate Change Strategy (Salgado, L., Dumas, M., Feoli, M., & Cedeño, M., 2013).

Forests and terrestrial ecosystems contribute significantly to climate change mitigation through theirs influence on the global carbon cycle acting as sinks storing large amounts of this element by means of biomass production and soil through the incorporation of organic matter, oxygen exchange carbon with the atmosphere through photosynthesis and respiration, but become a source of atmospheric carbon when under disturbances (Brown, 1997). The adequate determination of biomass in a forest is the basis to know the amounts of carbon in its components (Locatelli & Leonard, 2001). González-Zárate (2008), estimated biomass and carbon stocks in three cool temperate species : *Pinus maximinoi* H. E. Moore, *Pinus oocarpa* var. Ochoterenai Mtz. and *Quercus sp*. Allometric models were obtained from total biomass and components (stem, branches and foliage) based on variables such as DBH , total height in feet, height to top of the cup and crown diameter , calculating for *Pinus maximinoi* stands a storage of 161,97 Mg ha^{-1} and 81 Mg ha^{-1} of carbon. The stands with *Pinus oocarpa* fix 142,23 Mg ha^{-1} of biomass and 71 Mg ha^{-1} carbon. Similarly Nájera-Luna (1999), performed a study to adjust equations that help to predict biomass, stem volume growth and increment of biomass and carbon sequestration in ten typical species of Matorral Espinoso Tamaulipas in northeastern Mexico; the results showed that spatial level standing biomass was 51,45 Mg ha^{-1} with a distribution of 4% in foliage legs (61% in branches and 35% in stem), with an annual average above biomass production for the ten species is 4,11 Mg ha^{-1} yr^{-1}.

The information generated in such studies becomes doubly important since it allows knowing the amount of carbon stored in existing natural forests, and also reveals the potential of commercial and noncommercial plantations as the groundwork to manage it as environmental services (Schelegel, B., Gayoso, J., & Guerra, J., 2000). Usually allometric models are generated by species, but it is likely that several species growing on the same type of vegetation (which is our case) have similarities of morphological pattern of growth and therefore, in the allocation of aboveground biomass (Acosta-Mireles, M., Vargas-Hernández, J., Velázquez-Martínez, A., & Etchevers-Barra, J.D., 2002).

The main objective was to generate the best allometric equation(s) which to estimate aboveground biomass in *Eucalyptus saligna* and *Eucalyptus camaldulensis.*

Materials and method

Site and variables

Destructive sampling of 31 trees of *Eucalyptus saligna* and *Eucalyptus camaldulensis* planted within the Instituto Tecnológico de Costa Rica main campus, located in the city of Cartago was performed to obtain information on the diameter at breast height (DBH) and diameter at stump height (DSH) in cm, overall height (measured in m) and dry weight of leaves (WDL) in gr, to determine the effect to total tree biomass. Linear regression analysis included as predictor variables DBH, DSH and WDL was performed and total aboveground biomass as response variable, to then choose the best model to estimate average total aboveground biomass for a tree within the range of observations.

Statistical analysis

The descriptive analysis was made using box plots and histograms of each predictor and the response variable, as these graphics allow us to study both the dispersion and variability, and explore position measurements. It is very important to analyze the linear association between the response variable and each predictor, in order to determine which predictors are most appropriate for inclusion in the linear model. For this we considered a simple linear regression between the response variable and each predictor separately, and then build the partial graph of each model according to its corresponding predictor (Figure 1) waste, further to estimate the linear correlation coefficient for each pair of variables (Table 1).

For the selection of the best predictors variables, back and forward selection criteria, adjusted coefficient of determination R2, Akaike (AIC) , Bayes (BIC) and Mallow statistic (Cp) were used. All these criteria indicate that the best predictor model includes only the weight of the dried leaves. The linear regression model is estimated only with that predictor and although this meets the assumptions and the percentage of the variability of the biomass variable explained is approximately 95% ($R^2 \cong 0{,}95$), is not considered final model due to the estimation of the predictor variable is complicated and is conducted with sophisticated equipment of great value, which represents a much higher cost compared to recording other variables easily measured as a diameter or tree height.

It is very important to emphasize that the analysis used 30 observations, given than 29th observation was eliminated since represented a potential influence value on the adjusted general values.

Results and discussion

Descriptive analysis

It can be seen in the box plots for the variables : weight of dry leaves , DBH , DSH and ground biomass (left side of Figures A1 , A2 , A3 , A4 and A5) , that there is a value in each case (this corresponds to the observation 1), which departs significantly from the other observations , i.e. the value is positioned outside of the range with lower bound equal to the value which is less than 1,5 times the interquartile range with regard to the first quartile and upper limit equal to the value that is 1,5 times greater interquartile range over the third quartile, which does not happen with total Height. Furthermore, both the box plots and histograms for the variables: dry leaves weight and aboveground biomass (Figure A1 and A5) show a positive asymmetric behavior (the estimation of the respective average is greater than the corresponding median) with the same charts and histograms for DBH, DSH and total height (figures A2, A3 and A4) showing a negative asymmetric behavior. Particularly in Figure A1 it can be seen that the dry leaves weight varies between 100 and 3000 grams, however most observations are between 500 and 2000 grams, on the other hand Figure A2 shows that the average DBH is about 3,5 cm and the number of trees with DBH below average exceeds the number of trees with DBH above that value. Figure A3 shows that the diameter at the stump (DSH) ranges from 2 to 10 cm with an average of 5,5 cm; overall height ranges between 2 and 6 m with a 4,5 m average. Figure A4 shows the response variable values (aboveground biomass) varies between 400 and about 10000 grams, with a clustering of values less than 6000 grams for an average of 2800 grams. In general all the variables have large variability, this because the coefficients of variation (Table 2) are relatively high. In the graphs above is observed how the smoothed line does not fit very well to the regression line in most cases, but all correlation coefficients are greater than 0,7, which shows the existence of a significant linear influence of the predictors on the response variable.

Selection of variables

The selection of the dry leaves variable shows the importance of knowing how to estimate the weight of the dried leaves to predict tree biomass, because this predictor have a fairly linear relationship with the response variable. Excluding the dry leaves weight variable the selection criteria listed above for the selection of the best variables were used once more. The results show that the best model includes only the diameter variable stump

Table 1. Estimated coefficients of linear correlation between the response variable and each predictor.

Cuadro 1. Coeficientes estimados de correlación lineal entre la variable respuesta y cada predictor.

Predictor	Correlation coefficient
Dry leaves weight	0,9751
Diameter at breast height (DBH)	0,8353
Diameter at stump height (DSH)	0,8847
Total Height	0,7021

Table 2. Estimation of the coefficients of variation of the predictors and the response variable.

Cuadro 2. Estimación de los coeficientes de variación de los predictores y la variable respuesta.

Variable	Variation coefficient%
Dry leaves weight	68,47
Diameter at breast height (DBH)	36,30
Diameter at stump height (DSH)	27,23
Total height	23,01
Aboveground biomass	74,55

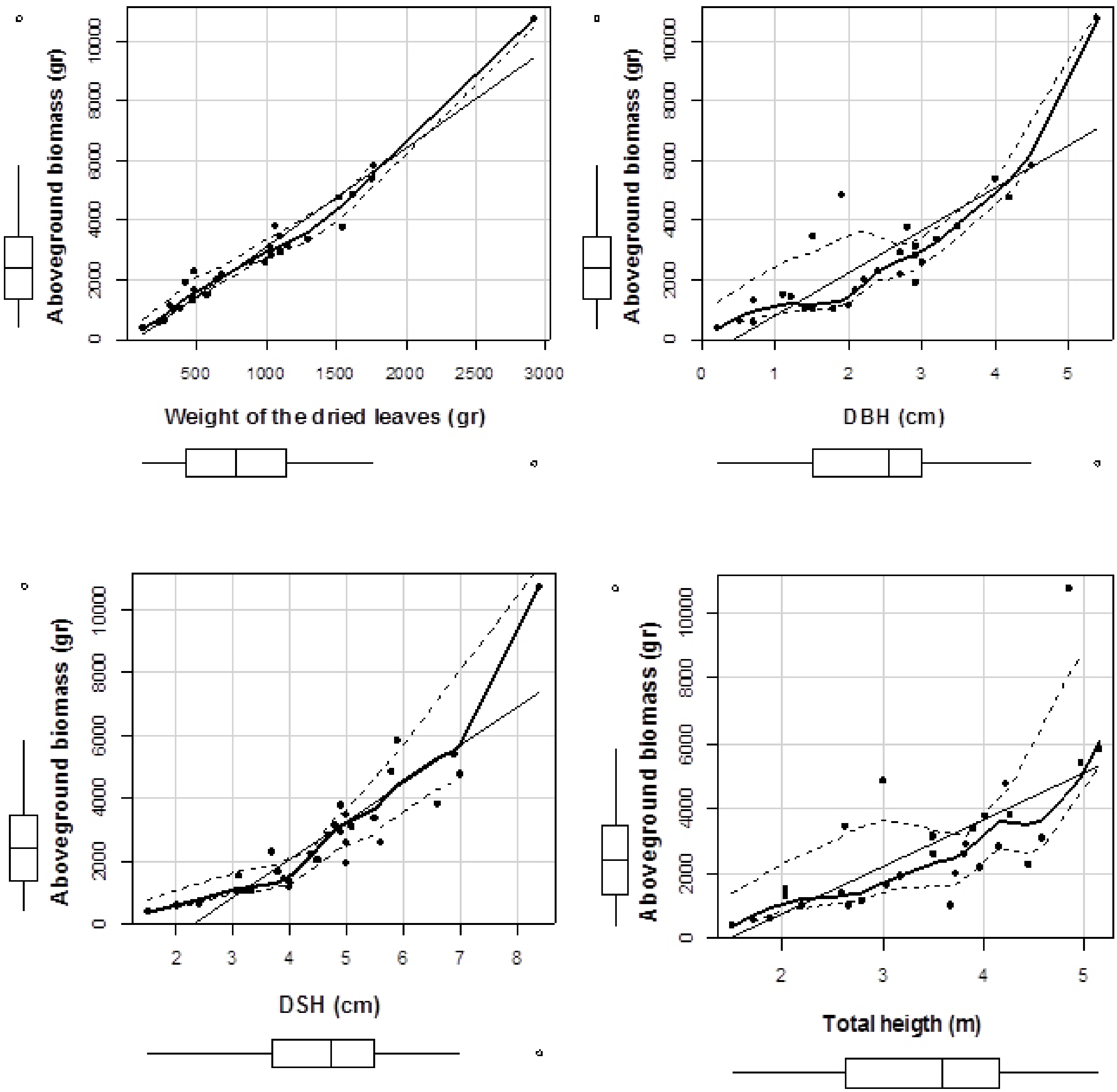

Figure 1. Residual partial depending on the variables: weight of dry leaves, DBH, DSH and total height respectively.

Figura 1. Residuos parciales dependiendo de las variables: peso de hojas secas, DAP, DAT, y altura total, respectivamente.

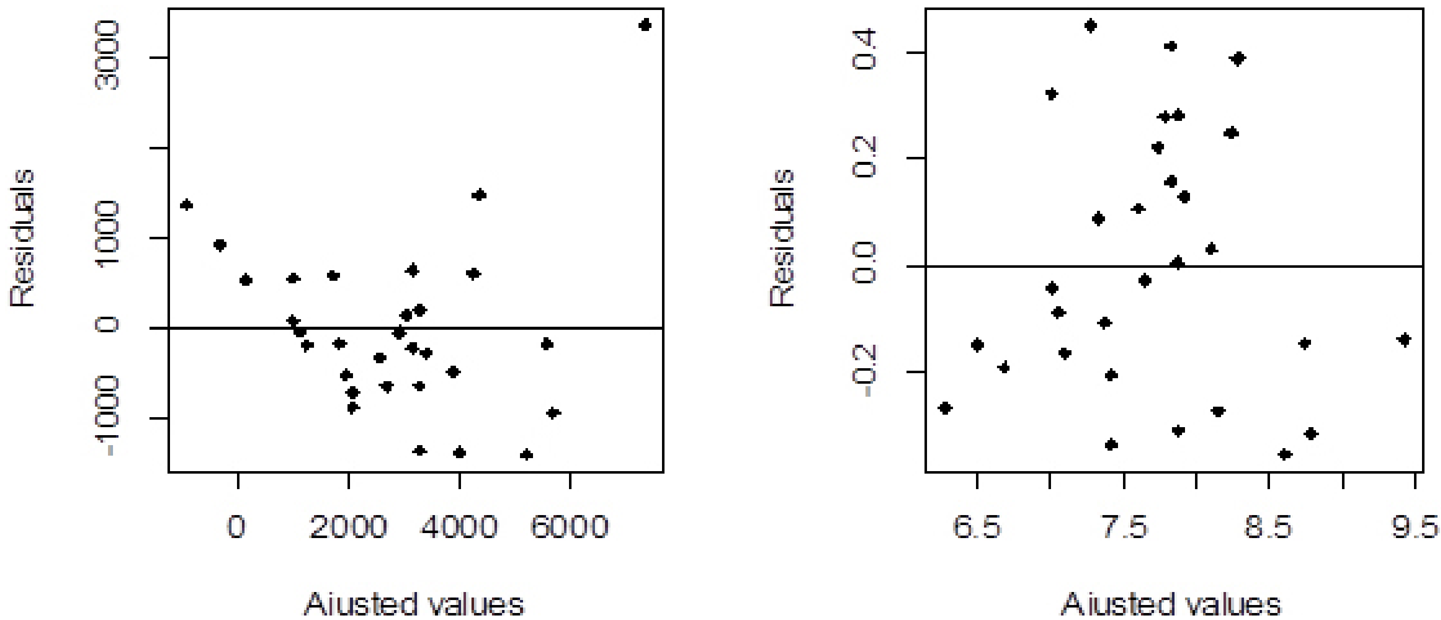

Figure 2. Residuals against fitted values obtained by applying the linear model that predicts the average biomass. Response to the left unprocessed, natural logarithm of the response to the right.

Figura 2. Residuos contra valores ajustados obtenidos al aplicar un modelo lineal para predecir la biomasa promedio. A la izquierda se observa la respuesta sin procesar, a la derecha se observa la respuesta con logaritmo natural.

height (DSH), and that this model has greater plausibility, that is, the sum of squares residual (SSR) is lower, the adjusted R^2 is higher and the model is unbiased compared with other models.

Verification of assumptions

Homoscedasticity or constant variance of errors.

Figure 2 shows the residuals versus the fitted values obtained by applying the linear model that predicts the average biomass. The caption at left shows the residuals and fitted values using the raw variable , where a curvilinear pattern is identified , which leads us to conclude that the constant variance assumption is not met, this is evidenced in a more formal way to apply the Breusch-Pagan test , which is not significant.

The right caption shows the residuals and fitted values using the natural logarithm to the response variable (such transformation was chosen because $\lambda = 0$ in the interval where the log-likelihood is maximized, this is noted in the Box-Cox transformations chart (Figure A6), this graphic evidences a constant variance since the behaviors of observation points is random, such result is confirmed through formal test of Breusch - Pagan significant.

Linear relationship between predictors and response

Figure 3 corresponds to the graph of the partial residuals of linear model based on the diameter at stump height (predictor) to determine whether there is a linear relationship between the predictor and logarithm of aboveground biomass (response). Left caption shows the relationship between the predictor and response without any transformation and right caption uses the square root of predictor. In both graphs the smoothed line is a linear behavior, which shows that the assumption of linearity is met. As the linear relationship improved by applying the square root predictor, it was decided to use the transformed variable in the linear model.

Table 3. Estimated coefficients and their corresponding standard error by: ordinary least squares, using 30 observations and robust regression using 31 observations.

Cuadro 3. Coeficientes estimados con su correspondiente error estándar según: mínimos cuadrados ordinarios, utilizando 30 observaciones y una regresión robusta utilizando 31 observaciones.

	Ordinary Least Squares		Robust Regression	
Coeficient	Estimation	Standard Error	Estimation	Standard Error
Intercepto	2,6915	0,3072	2,8563	0,3563
√Dat	2,1338	0,1298	2,0674	0,1517

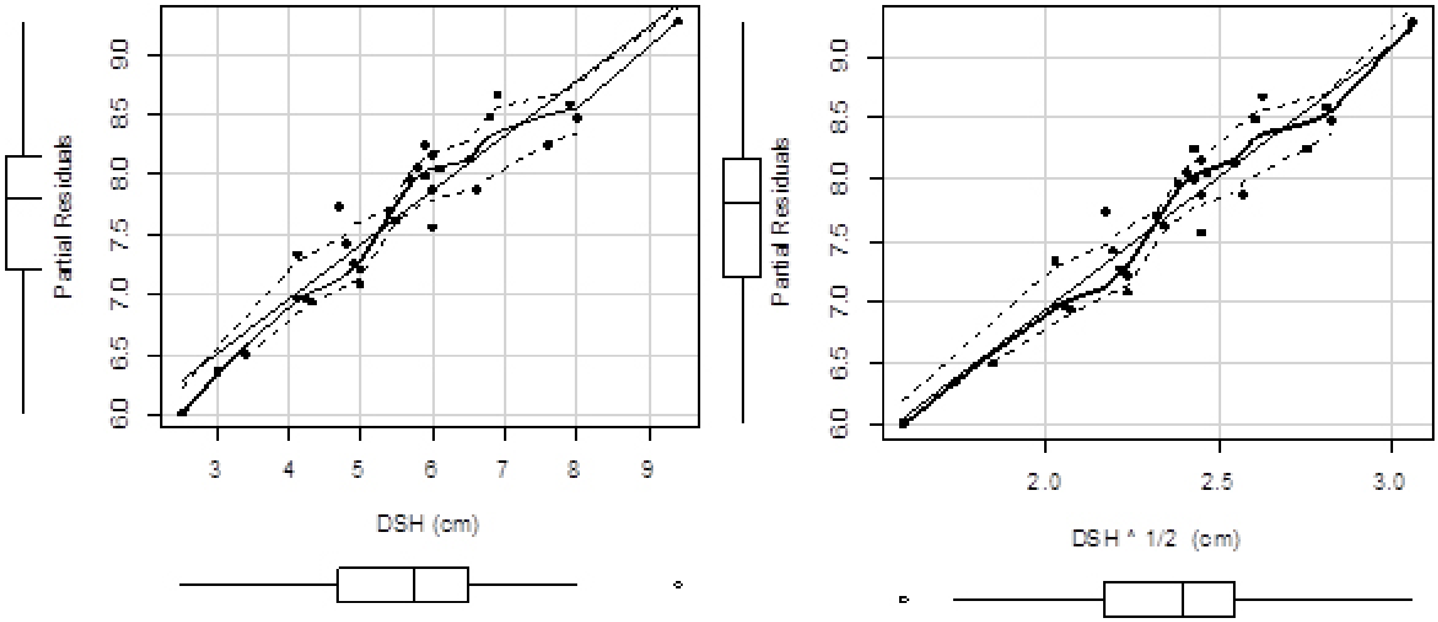

Figure 3. Partial residuals obtained by applying the linear model that predicts the average biomass against: predictor unprocessed left; square root predictor on the right.

Figura 3. Residuos parciales obtenidos al aplicar un modelo lineal para predecir biomasa promedio contra: un predictor sin procesar, a la izquierda; un predictor utilizando la raíz cuadrada, a la derecha.

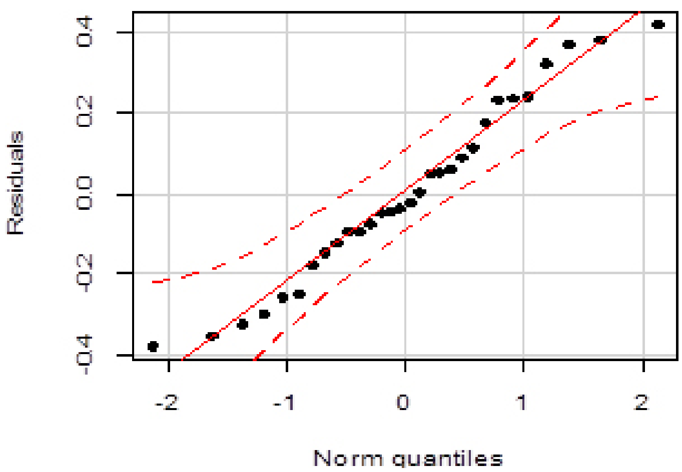

Figure 4. Residuals obtained by applying the linear model that predicts the average aboveground biomass as a function of the expected standard normal quintiles.

Figura 4. Residuos obtenidos al aplicar un modelo lineal para predecir la biomasa en pie promedio sobre el nivel del suelo en función de los quintiles normales estándar esperados.

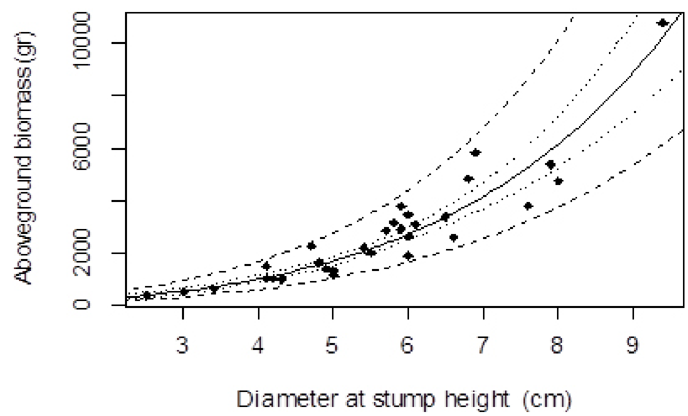

Figure 5. Data from 30 trees (dots) with the model prediction (black line) and confidence intervals for a tree taken at random (dotted lines) and the average tree (dashed lines).

Figura 5. Datos de 30 árboles (puntos) con el modelo de predicción (línea negra continua) y los intervalos de confianza para un árbol tomado al azar (líneas punteadas) y el árbol promedio (línea discontinua).

Normal distribution of errors (normality)

Figure 4 demonstrates a linear behavior around the plotted points, which is within the expected (confidence bands) variation. This is evidence that the normality assumption of the errors is met. Shapiro -Wilk normality test was also applied to the residual of the linear model and it was significant.

Extreme values and cases of influence

To identify outliers externally student residuals are analyzed graphically (Figure A7), showing that there are no observations that can be regarded as outliers, since no residual has a larger magnitude with respect to the maximum value set. Moreover it is analyzed graphically the existence of potential values of influence in three ways on its own adjusted value (Figure A8), on the regression coefficient (Figure A9) and all the fitted values (Figure A10). For the first two aspects no values are considered to be influence values because no value exceeds the limits, for the third aspect value corresponding to the tree number 7 constitutes a value of influence are observed, but the influence is not relevant as to apply remedial measures.

Initially there were 31 observations , given that observation number 29 had a potential influence on the fitted values of the model (Figure A11) , we proceeded to estimate the model using robust regression , and then compare the coefficients and their corresponding standard errors, with their counterparts using the method of ordinary least squares without considering observation 29. It can be seen in Table 3 that both the estimate of the intercept and the regression estimate coefficient of the square root variable DSH do not differ much from one method to another, but the standard error increases when using robust regression, thus it was so decided to eliminate the above-mentioned observation.

Final model and validation

The following equation corresponds to the final model selected:

$$Bio\hat{m}asa_i = e^{2,6915+2,1338\sqrt{DSH_i}}$$

Notably, the percentage of the biomass variability explained by the model (coefficient of determination R^2) corresponds to 90,61% , besides the mean error square (MSE) is approximately 0,0526 and the predictive power of the model (P^2) equals 0,9021.

For model validation no new data was collected since the harvest of new individuals carries a significant cost, both economic and environmental, so the model is re-estimated 30 times using 29 observations on each of the estimation runs data (one observation was excluded on each different estimate) and the mean squared prediction error (MSPR), estimating the observation that was not considered in each case. Finally, the average value is calculated to obtain an average MSPR of about 0,0548 MSPR very close to MSE, so we conclude that the latter is not biased.

Figure 5 shows the average biomass estimated using the final model. Confidence intervals for the mean response (green lines) and confidence intervals for individual values (red line) are observed within the range of variation in the observed data. It is observed that the average biomass tends to increase by an exponential relationship, where the diameter at stump height increases.

Forest growth models may comprise many separate but interrelated components, each of which may influence, and be influenced by other components and by assumptions in the-model. Model evaluation should extend to all model components and assumptions, and this requires a thorough understanding of the structure of the model and the interrelationships between components (Soares, P., Tomé, M., Skovsgaard, J.P., & Vanclay, J.K.*,* 1995); understanding the behavior of allometric variables prior to model construction is a fundamental step to decide what variable might be best suited for which stage of the plantation. Biomass for energy plantations, such as the one analyzed in this paper, relies better on the use of DSH as a predictor of aboveground biomass given the age and the coefficient of variation present. Total height although having a low variability is not dependent on density and thus might me a weak predictor on rotation terms. However, evaluation of which variable to use should not be a mere afterthought to model construction, but should be considered at every stage of model design and construction; for example when component functions are formulated and fitted to data, and when these components are assembled to provide the completed model (Soares et al*.,* 1995).

The model here constructed is an individual tree biomass model; it must be remembered that as class width becomes wider and the number of trees per cohort increases, the distinction between individual tree models and size class might be blurred; single tree models are defined as those which simulate each individual for a given period (Vanclay, 1994). Understanding the initial behavior of a bioenergy plantation such as this with regression models would eventually aid in the development of stand models for fast growing plantations and they would aid at validating their use.

Other studies (Almeida, A.C., Landsberg, J.J., Sands, P.J., Ambrogi, M.S., Fonseca, S., Barddal, S.M., & Bertolucci, F.L., 2004 ; Esprey, L.J., Sands, P.J., & Smith, C.W.*,* 2004) have ventured in the use of process based models to predict Eucalyptus plantations productivity in new areas, analyzing changes in productivity across currently planted areas and to determine whether such changes are attributable to climate or management, and as a tool for defining strategic scenarios. Undeniably, they have acquired the capacity to provide immediate information about growth in any area of a large plantation estate; however their use still comes to restriction concerning calibrations, therefore without information on individual behavior of trees under new densities and conditions many of these models risk potential failure; making basic studies for high density planting for biomass production, as the one performed here, abundantly necessary.

Conclusions

The tight end allometric equation to estimate biomass by OLS in species *Eucalyptus saligna* and *Eucalyptus camaldulensis* based on diameter at stump height (DSH) has a high degree of reliability according to the analysis carried out and the estimated parameters.

The model obtained on this study is an individual tree model useful for short rotation biomass crops for this geographical region; which will be of extreme use for energy enterprises in need of biomass estimations.

Recommendations

To complement the information on carbon in the species studied, it is recommended to evaluate biomass related to and soil organic matter, to have a complete assessment of carbon storage for eucalyptus ecosystems.

It is critical , in future studies to estimate aerial biomass , to accurately measure dry leaves weight since this variable is a predictor of high quality, also considering variables such as diameter (DBH) and overall height, as these relate very well with aboveground biomass of trees.

Studies should be conducted on quantification of biomass with other eucalypts elsewhere in the country, to make comparisons between species or between sites taking into account the different environmental factors that can influence reforestation projects

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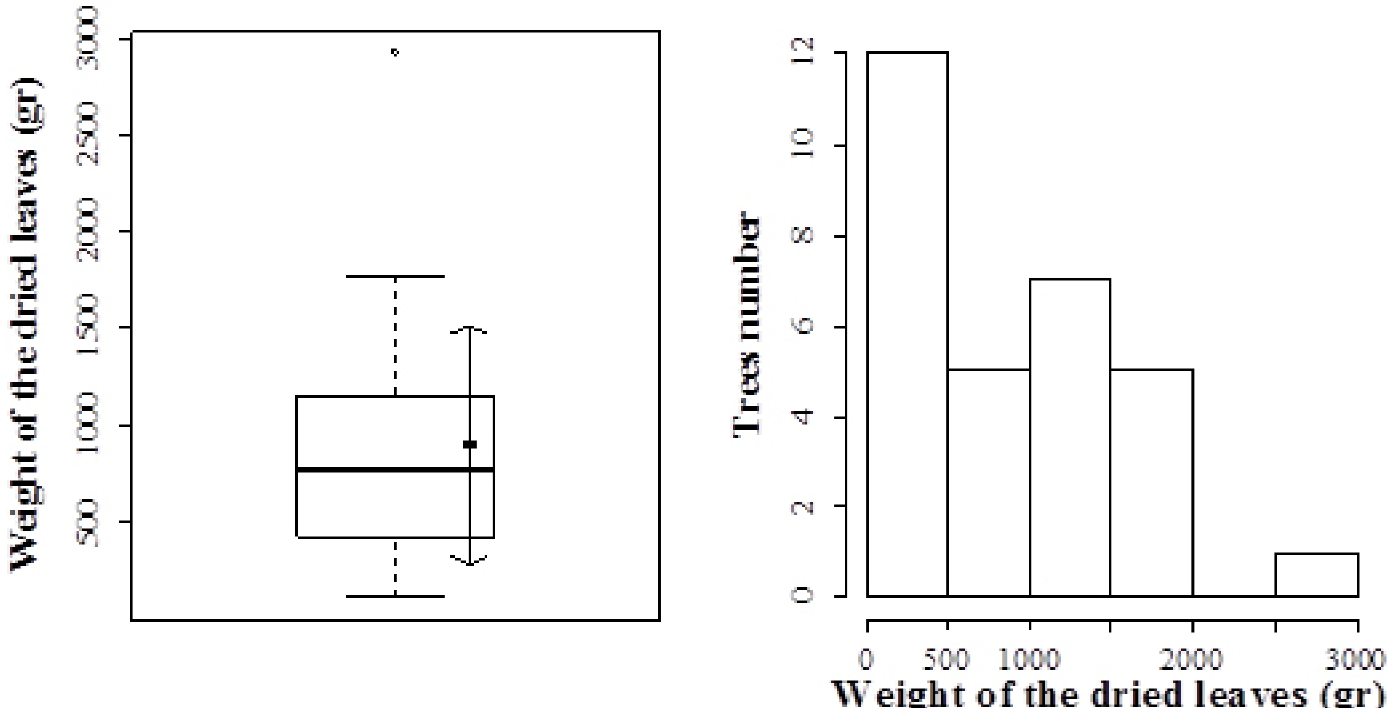

Figure A1: descriptive graphics for the variable dry leaves weight.

Figura A1: gráficos descriptivos para la variable peso de hojas secas.

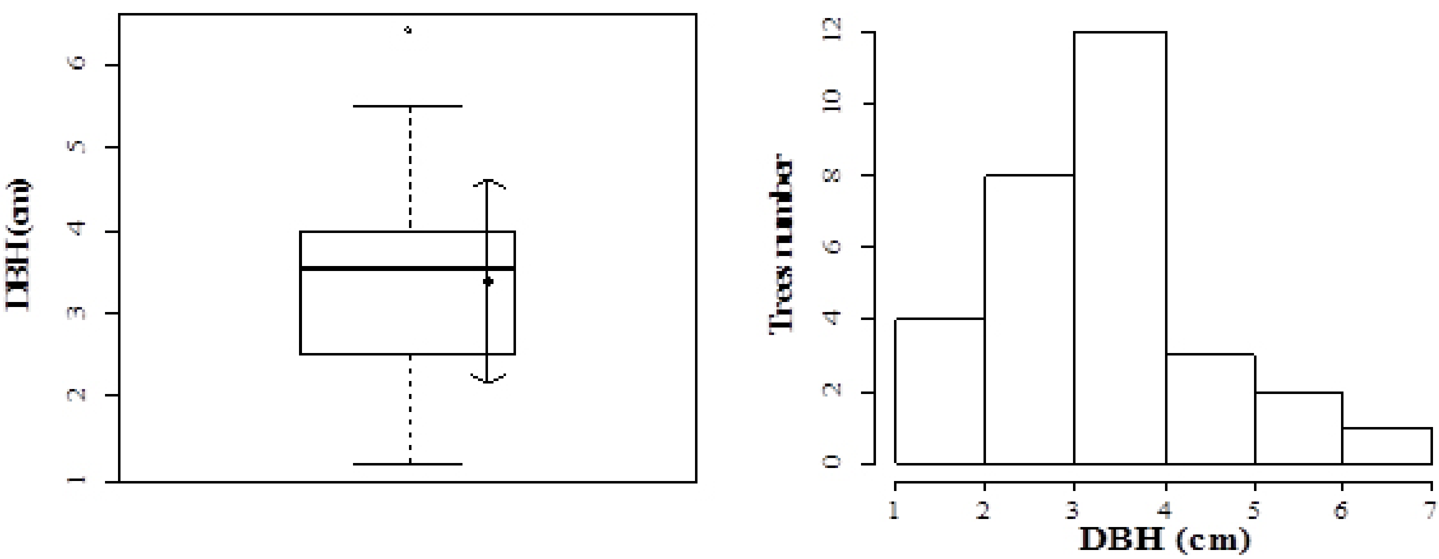

Figure A2: descriptive graphics for the variable diameter at breast height (DBH).

Figura A2: gráficos descriptivos para la variable diámetro a la altura del pecho (DAP).

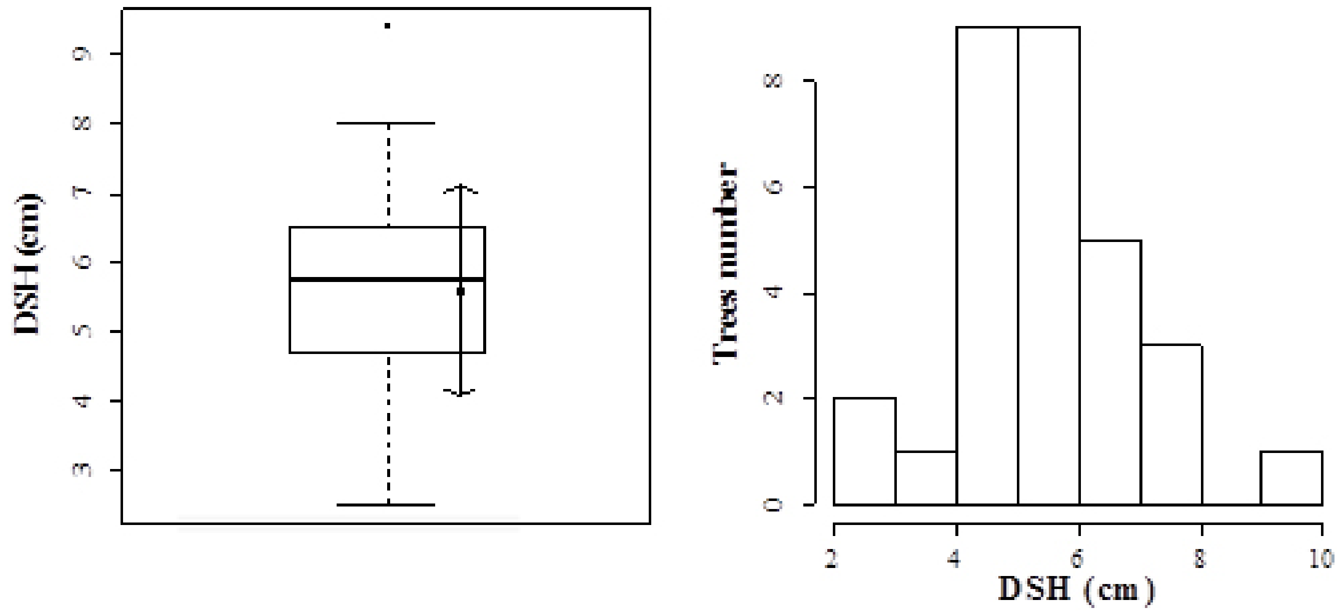

Figure A3: Descriptive Charts for variable diameter at stump height (DSH).

Figura A3: Gráficos descriptivos para la variable diámetro a la altura del tocón (DAT).

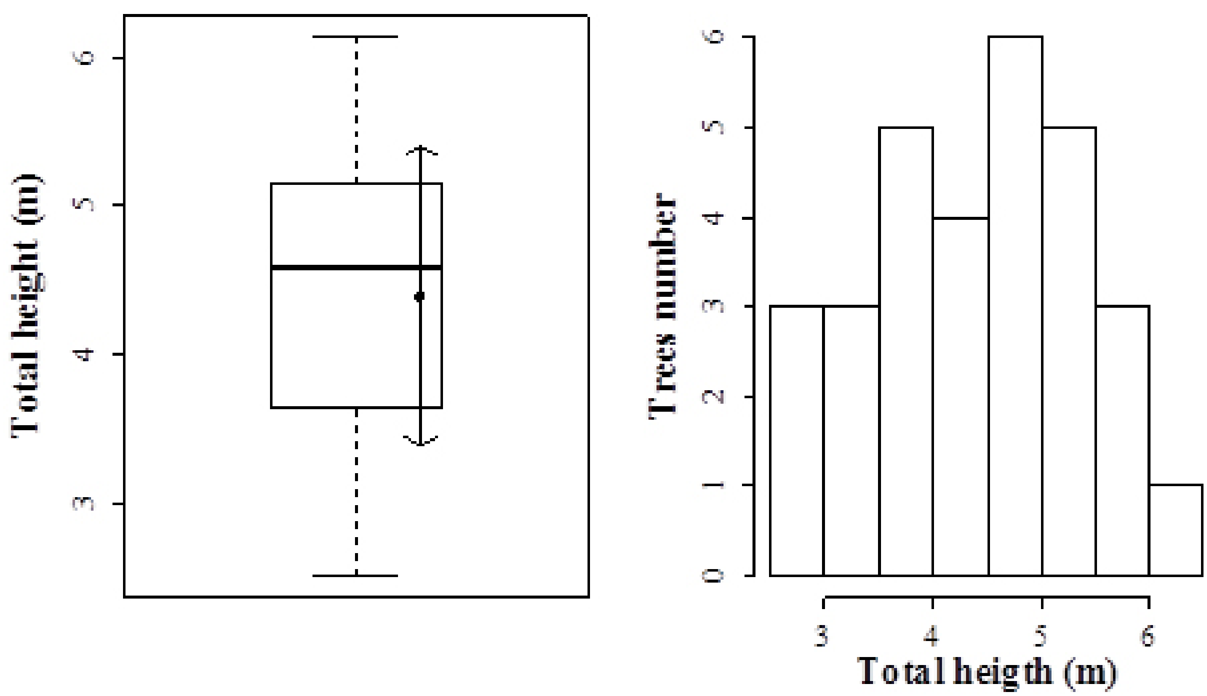

Figure A4: Descriptive Charts for total height variable.

Figura A4 : Gráficos descriptivos para la variable altura total.

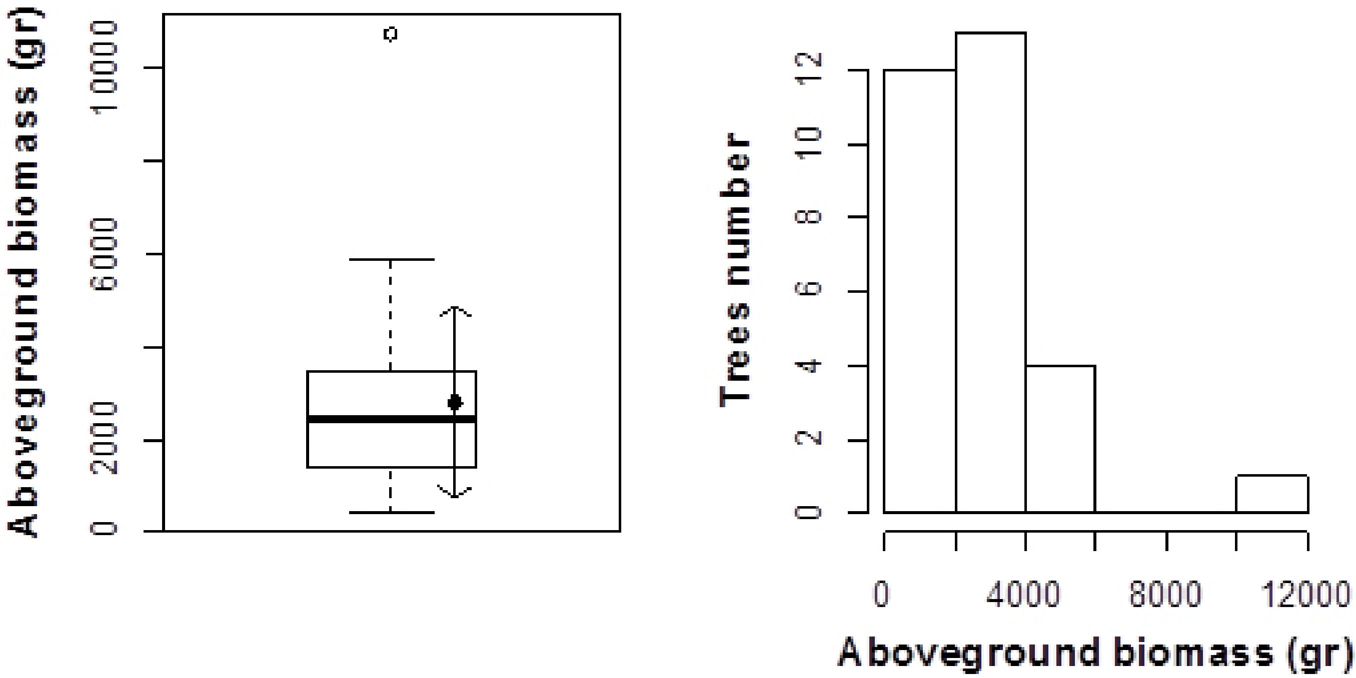

Figure A5: Descriptive charts for above ground biomass variable.

Figura A5: Gráficos descriptivos para la variable biomasa en pie sobre el nivel del suelo.

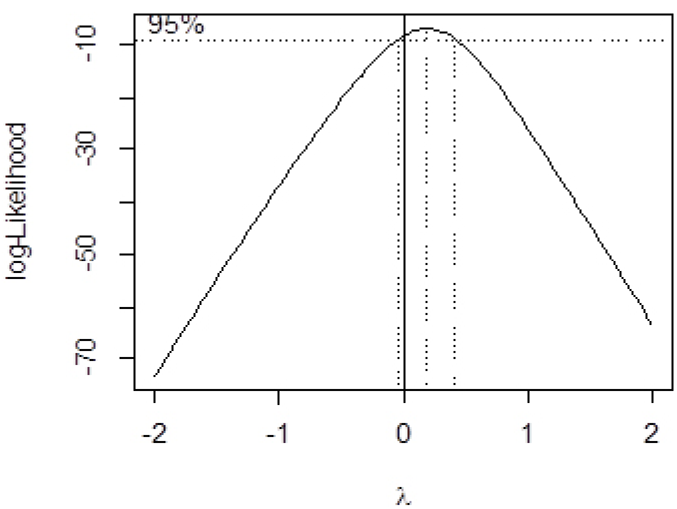

Figure A6: Values of λ for Box -Cox transformations.

Figura A6: Valores lambda para transformaciones Box –Cox.

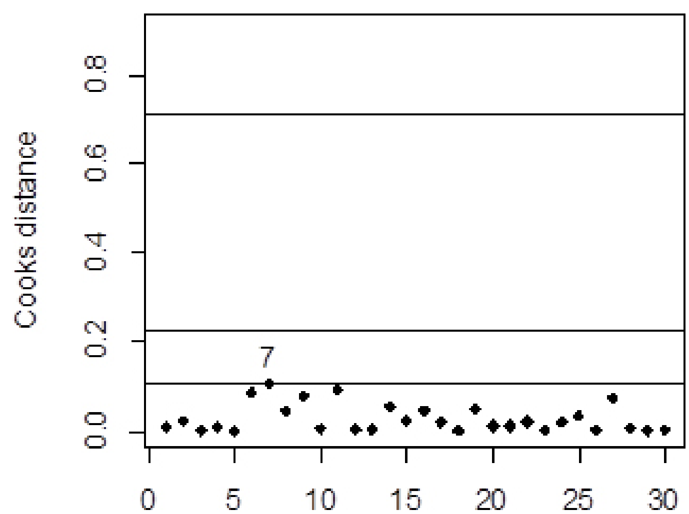

Figure A7: Studentized residuals externally obtained through the application of the linear model that predicts the average aboveground biomass.

Figura A7: Residuos estudentizados obtenidos externamente a través de la aplicación de un modelo lineal para predecir la biomasa en pie promedio sobre el nivel del suelo.

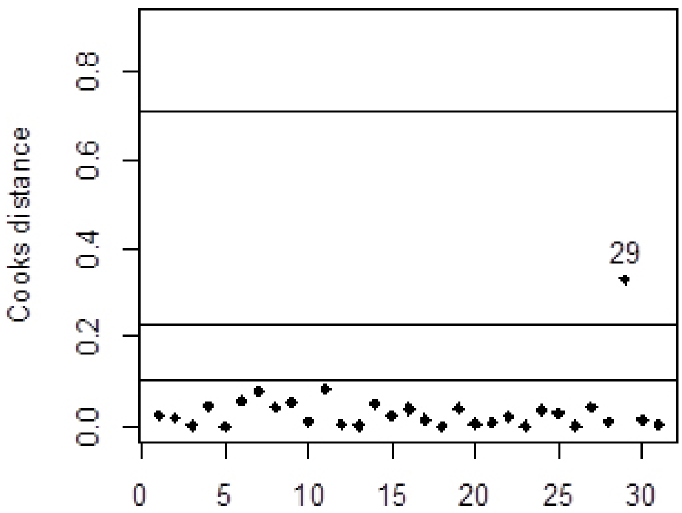

Figure A8: DFFITS values obtained by applying the linear model that predicts the average biomass.

Figura A8: Valores de DFFITS obtenidos al aplicar un modelo lineal para predecir la biomasa promedio.

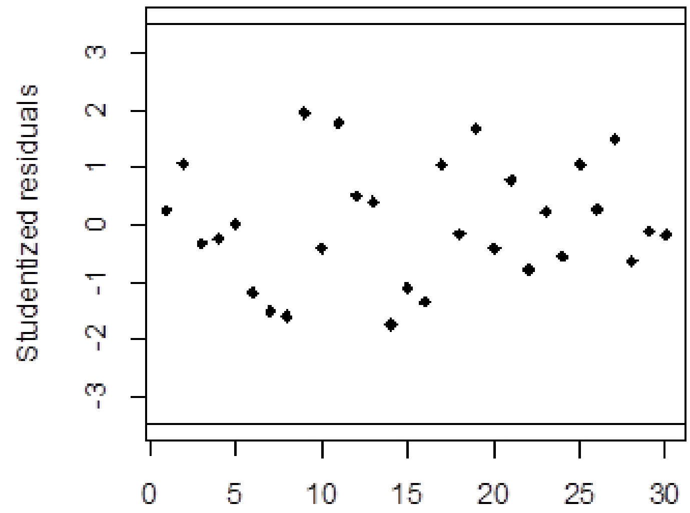

Figure A9: dfbetas values obtained by applying the linear model that predicts the average biomass.

Figura A9: valores dfbetas obtenidos al aplicar un modelo lineal para predecir la biomasa promedio.

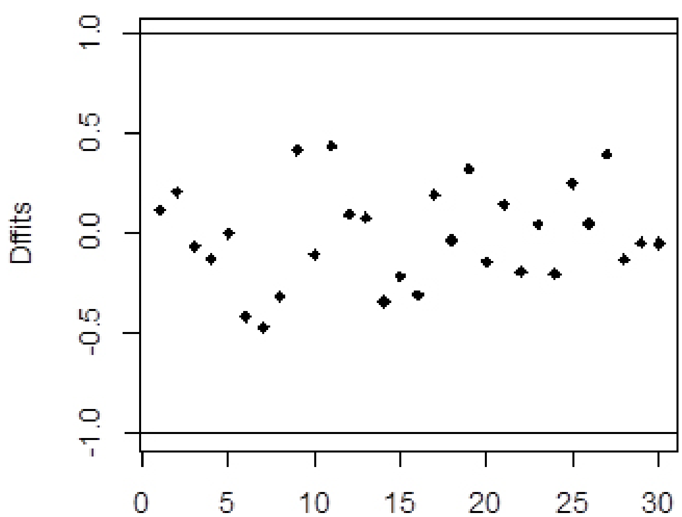

Figure A10: Cook distance values obtained by applying the linear model that predicts the average biomass.

Figura A10: Valores de la distancia de Cook obtenidos al aplicar un modelo lineal para predecir la biomasa promedio.

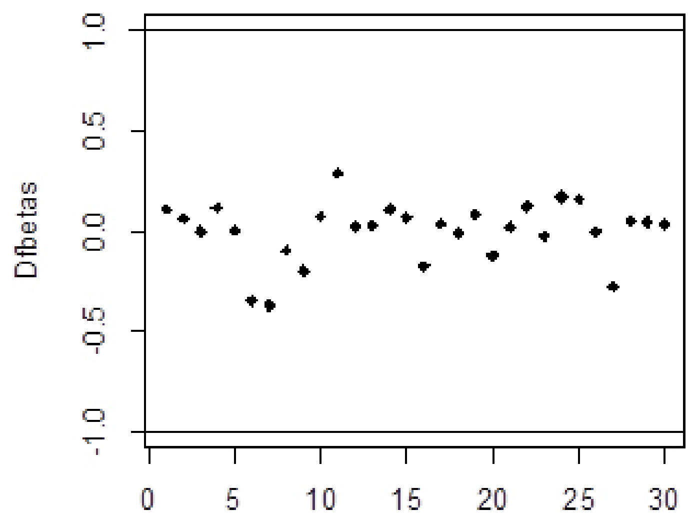

Figure A11: Cook distance values obtained by applying the linear model that predicts the average biomass using 31 observations.

Figura A11: Valores de la distancia de Cook obtenidos al aplicar un modelo lineal para predecir la biomas promedio utilizando 31 observaciones.